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Abstract

This paper investigates when trade could cause the selection effect. Since the increased average real wage induced by trade triggers the selection effect in Melitz (2003), the main issue is the labor market conditions under which trade raises the average real wage. To identify the labor market conditions for the selection effect, this paper employs worker heterogeneity with respect to abilities in Blanchflower, Oswald, and Sanfey's (1996) rent-sharing framework. This simple model plays a crucial role in building estimation equations that use the residual wage in order to reflect worker heterogeneity. According to the results of regressions of the average and 10th percentile of residual wages, this paper shows that with high union density, low job destruction, and low job creation, the effect of trade on the average residual wage is likely to be negative because the impact of imports exceeds that of exports. Moreover, the impact of trade on the average wage must work through the residual wage because this study does not find a significant impact of trade on the average predicted wage. As a result, the more rigid the labor market is, the less likely trade is to raise the average industrial wage and the less likely the selection effect in Melitz (2003) is to occur.

JEL Classification: F16; J31; C23
Key Words: Trade, Residual wage, Selection effect, U.S.

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I. Introduction

The aggregate productivity gains from trade liberalization can be boosted mainly by the reallocation process of domestic resources toward more productive firms, i.e. the selection effect of trade.[1] Felbermayr, Prat, and Schmerer (2008) have attempted to connect the aggregate productivity gains with the long run impact of trade on the labor market outcomes; that is, as long as the selection effect of trade exists, trade liberalization lowers unemployment and raises the real wage in the long run. This consideration on the aggregate productivity dynamics could shed new light on the early debates focusing on the short run and static impact of trade on labor market outcomes. However, trade does not always induce the selection effect in long run equilibrium. Certain conditions in a period of transition need to be satisfied. Otherwise, the selection effect may not occur, or even a negative selection effect might occur, as suggested in Archarya and Keller (2008) and Melitz and Ottaviano (2008). In particular, this paper suggests that the labor market can be involved in determining the extent to which trade causes the selection effect in the long run. As a result, to investigate the long run impact of trade on the labor market outcomes, we should focus on the labor market conditions in the transition path of selection effect.

This paper attempts to identify the labor market conditions that induce the selection effect of trade. Accordingly, this builds on Melitz (2003) that suggests the labor market

[1] In this paper, the selection effect implies a positive selection effect.

competition as a mechanism to cause the selection effect of trade.[2] Melitz's (2003) argument on the selection effect is that the increase in average real industrial wage induced by exports pushes up the aggregate productivity through taking the least productive firms out of the market. That is, the increased average real wage triggers the selection effect. Surprisingly, despite the critical role of the increased average real wage, little is known about the impact of trade on the average real industrial wage from the viewpoint of aggregate productivity dynamics. Accordingly, the main question that this paper investigates empirically by using U.S. data is as follows: under which labor market conditions does trade raise the average real industrial wage?

Recent theoretical attempts to employ worker heterogeneity in international trade models could help to identify labor market conditions due to explaining firms' and workers' heterogeneous responses to trade. Davidson, Matusz, and Shevchenko (2008) show that as the economy becomes more open to trade, how high ability workers in non-exporting firms respond to exporting firms' better offer relatively to non-exporting firms. Also, Helpman, Itskhoki, and Redding (2009) explain why firms in trade liberalization screen and fire workers with ability below the cut-off, and further how firms and workers share the firm's profit according to abilities.[3] Eventually, these studies imply that the compensation for a worker's ability could be the worker's and firm's most important criterion to make economic

[2] Archarya and Keller (2008) and Melitz and Ottaviano (2008) consider product market competition as an alternative mechanism to cause the selection effect.
[3] Here, the concept of ability in the above theoretical papers implies unobserved skills more than observed skills such as education and experience.

decisions. However, how can we handle worker heterogeneity with respect to abilities in an empirical study? Generally, econometricians cannot observe a worker's heterogeneous abilities directly. So there is little empirical evidence despite some theoretical attempts. In this situation, a good alternative is the residual wage stemmed from the Mincerian wage equation because the residual wage reflects the compensation for a worker's ability.[4]

To understand the relationship between abilities and the residual wage, this paper introduces worker heterogeneity with respect to abilities into Blanchflower, Oswald, and Sanfey's (1996) rent-sharing framework. According to this model, the residual wage is determined by a firm's profit and by individual bargaining power that comes from abilities;[5] that is, it reflects the compensation for workers' abilities that are evaluated by a firm. Therefore, although we cannot observe workers' abilities empirically, the residual wage enables us to estimate heterogeneous responses of firms and workers to changes in the compensation for workers' abilities. Particularly, provided that firms' profits and productivities are identified, ability cut-offs in firms can be compared to each other.[6]

How can the residual wage explain the firm's decision to fire and hire workers?

[4] Mincerian wage equation is used to estimate the premium of observed skills such as education and experience. The residual wage is empirically defined by the residual term in Mincerian wage equation. Therefore, it is likely to be connected to unobserved skills that affect the wage. Although the more popular term in studies on residual wage is unobserved skills, this paper uses ability instead of unobserved skills in order to link with theoretical studies on worker heterogeneity.

[5] This is similar to Lemieux (2006)'s assumption that residual wage is the product of abilities and compensation for them because firm's profit is related with firm's ability of compensating for unobserved skills.

[6] Firms with high productivity can cover huge recruiting cost to hire high-ability workers, while unproductive firms cannot afford to pay high recruiting cost. Therefore, unproductive firms are more likely to hire workers with low abilities than firms with high productivity because the adverse effect could be in unproductive firm's recruiting process. Therefore, this paper assumes that the cut-off is closely related to firm's productivity as suggested in Helpman, Itskhoki, and Redding (2009).

When a firm is faced with decreasing profit, it will lay off workers with low residual wages because those workers are evaluated as being less valuable by the firm. In other words, the residual wage reflects how the firm sorts its workers in terms of their performance. Also, in hiring workers to respond to increased market share, the firm would attempt to screen job applicants with abilities below the cut-off.[7] In the case of a worker's decision, the residual wage implies that workers with the same education level and experience could be paid differently according to the firm's profit, which can explain the motivation to search for a better job. If high-ability workers are in an unproductive firm, they would have the motivation to move toward a more productive firm in order to earn more compensation in the individual bargaining. As a result, the firm's and worker's decisions respond to changes in the firm's profit in a rent-sharing framework, which causes job flow.[8]

Trade liberalization affects firms' profits according to their productivity (Melitz, 2003). Thus, as the economy becomes more open to trade, firms and workers would make heterogeneous responses to the changes in the profit, which would determine the average residual wage at the industrial level. These responses suggest two main channels through which trade affects the average residual industrial wage: the change in the firm's profit and job flow. Without considering job flow, the influence on the residual wages of the change in a

[7] According to Huang and Cappelli (2006), firms can evaluate job applicants' abilities by using popular screening practices such as reference letters and obtaining the agent's past histories through credit bureaus or hiring detectives.

[8] Krueger and Summers (1988) and Gibbson and Katz (1992) focus on the reallocation of workers from low to high wages industries; that is, they examine why workers with the same education level and experience are paid differently in different industries. The residual in this paper explains why the workers move from unproductive firms to more productive firms in the same industry as well as across industries.

firm's profit from trade is obvious: imports lower the workers' residual wages because imports make the firm's market share shrink. In a similar way, exports raise the workers' residual wages.

However, in considering the job flow, the impact of trade on the average residual wage is more complicated. In the case of exports, the direction of each channel's impact is positive. With higher exports, exporting firms can make better offers to both inside and outside workers. Therefore, the workers who are compensated less relative to high abilities have the motivation to move toward exporting firms voluntarily due to the increased chances of obtaining a better job;[9] that is, it implies that the impact of job flow would depend on the magnitude of job creation in exporting firms. In sum, the impact of exports on the average residual wage is positive. And the residual wage is more dispersed and left-skewed as job creation in exporting firms is working actively.

On the other hand, the impact of imports on the residual wage distribution depends on the magnitude of each channel's effect. Through a firm's profit *i.e.* one of two main channels, imports lower the residual wages. However, increased imports also make the marginal workers in firms and the workers in marginal firms exit the market.[10] The effect of this job destruction is to raise the average residual wage at the industry level. That is, the directions of the two channels' effects are opposite. Therefore, there is still the possibility of

[9] Davidson, Matusz, and Shevchenko (2008) also argues that as the salary gap between exporting and non-exporting firms is widen due to increased exports, the workers with high ability have more motivation to move toward exporting firms.

[10] The case of marginal workers is similar to the cleansing effect in recession (Barlevy, 2000).

removing the negative effect of import on the average (residual) wage without controlling for job destruction.[11] Unlike exports, with imports, the higher the job destruction, the less the residual wage is dispersed.

For empirical work, I use four datasets: Merged Outgoing Rotation Groups Current Population Survey (MORG-CPS), U.S. Trade by Feenstra (1998), Job Creation and Job Destruction by Foster, Haltiwanger, and Kim (2006), and Manufacturing Industry Productivity Database by Bartelsman, Becker, and Gray (2000).[12] The MORG-CPS provides us with a huge dataset as well as a less noisy measure of the key variable of interest (compensation per hour) relative to March CPS or PSID (Lemieux, 2006). This is important because this paper restricts the sample to full-time male workers in the manufacturing sector and obtains the residual wage from hourly wages by using the Mincerian wage equation. The dependent variables are the average and 10th percentile of estimated residual wage. Those dependent variables and explanatory variables such as job flow enable us to understand how the residual wage distribution is changed by trade and examine the labor market conditions under which trade raises the average residual wage at the industry level.

[11] Revenga (1992) summarizes and criticizes the early literatures which show insignificant or small impact of imports on the wage and employment (for example, Mann (1988), Grossman (1987)). In addition, Leamer and Levinsohn (1995) point out that Grossman (1987)'s methodology lacks treatment of cross-industry effects in estimating import price elasticity. However, due to job flow, there is the possibility of the positive relationship between imports and the average (residual) wage. This can be connected to the results in Ebenstein, Harrison, McMillan and Phillips (2009). They examine why the impact of import penetration on wages is empirically small despite having a relatively large impact on employment. They focus on the workers that transfer across industries. After controlling for the occupation-specific effects, they find a significant and negative impact of import penetration on individual wages

[12] While investigating the relationship between manufacturing wages and international trade, Gaston and Trefler (1994) use the CPS in order to reflect the characteristics of individual workers in the industry. Recently, Ebenstein, Harrison, McMillan and Phillips (2009) and Liu and Trefler (2008) have attempted to link industry-level data on offshoring activies of U.S. multinational firms, import penetration, and export shares with the CPS.

Since it is difficult to measure trade liberalization by changes in policy, generally, the alternative ways are to use the trade openness, transaction costs, tariffs and so on. Basically, this paper attempts to capture trade liberalization by using import penetration, export propensity, and the real industrial shipment.[13] Particularly, the real industrial shipment would control for third factors such as changes in consumer's taste and technology. Furthermore, this paper uses U.S import weighted average tariffs for the robustness check of measuring trade liberalization.

This paper employs the dynamic panel model in order to reflect the persistence of residual wage distribution.[14] According to Cameron and Trivedi (2005), the within estimator cannot control the endogeneity problems induced by the use of the lagged dependent variable as the explanatory variable, the measurement error in pseudo panel and the reverse causality. In order to avoid those endogeneity problems, I employ the system GMM (General Method of Moments) proposed by Blundell and Bond (1998). In particular, I use Bowsher's (2002) suggestion and the standard error corrected by Windmeijer (2005) in order to avoid overfitting bias and the small sample bias, respectively.

I find that the import penetration lowers the average residual wage, but the export propensity raises the average residual wage. The impact of import penetration especially depends on the level of job destruction, while that of export propensity depends on the level

[13] Import penetration is the share of import in domestic consumption *i.e.* (imports)/(shipment+imports-exports). Export propensity is also the share of exports in domestic production *i.e.* (exports)/(shipment+imports-exports).
[14] Since some interviewers in MORG-CPS can be observed between two years, the variables of interest are likely to be persistent.

of job creation. When much job destruction occurs, the impact of import penetration on the average residual wage changes toward being positive. This interesting result is also supported by the evidence in the regression of the 10th percentile. Particularly, the evidence on the regression of the 10th percentile of residual wage shows that the left-tail of residual wage distribution will be cut as more job destruction occurs.

In addition, as job creation increases, the impact of export propensity on average residual wage is more positively sizeable. This is expected in Davidson, Matusz, and Shevchenko (2008) and Helpman, Itskhoki, and Redding (2008); that is, in response to increased exports, exporting firms hire workers with abilities above the cut-off rather than the unemployed. Therefore, despite job creation induced by exporters, workers with abilities below the cut-off are still likely to be unemployed.

In sum, this paper shows that with high union density, low job destruction, and low job creation, the effect of trade on average residual wage is likely to be negative because without active job flow, the imports' negative impact on residual wages exceeds the exports' positive impact on residual wages; that is, trade liberalization is likely to be negatively associated with average residual wage in the more rigid labor market. In addition, this paper attempts to check the robustness of those results by measuring trade liberalization as the degree of tariff and finds the consistent results.

Moreover, to link those results with the impact of trade on average real industrial wage, this paper runs the regression of the predicted average wage on import penetration and export propensity.[15] According to the results, trade has an insignificant impact. It is expected by the fact that the Mincerian wage equation does not reflect industrial characteristics. So the impact of trade on the average industrial wage is determined only by the residual wage. Consequently, since trade liberalization in the more rigid labor market does not increase the average industrial wage, the selection effect is unlikely to occur and so worker's welfare under those conditions would not be raised in the long-run.

The rest of the paper is organized as follows. In Section 2, I show the conceptual framework in order to understand how worker and firm make their decision according to residual wage. I present a description of the dataset and the estimation strategy in Section 3. Section 4 contains the results from regressions of several dependent variables on the import penetration, export propensity, and job flow etc. Section 5 shows the result of robustness check. Section 6 concludes.

II. An Illustrative Model

The purpose of this section is to understand i) how the residual wage is determined and ii) which trade affects the average residual wage at the industry level through channels. For this, I modify Blanchflower, Oswald, and Sanfey (1996) by making the worker's bargaining power dependent on his/her ability and employing the production function in

[15] The average real wage can be decomposed into the predicted average wage and the residual average wage.

Helpman, Itskhoki, and Redding (2008).[16] This model is simple, but useful in deriving implications for estimation.

Helpman, Itskhoki, and Redding (2008) effectively use the following production function to describe why the firm attempts to screen workers with abilities below the cut-off:

$$y = \theta h^{\gamma} \bar{a}\,, \quad 0 < \gamma < 1\,,$$

where θ is firm's productivity, h is the labor supply, a_i is the worker i's ability, and the average of workers' abilities in a firm, $\bar{a}$. Worker ability (a_i) and firm's productivity (θ) are assumed to be drawn from a Pareto distribution, with cumulative distribution function, $G_a(a) = 1 - (a_{\min} / a)^k$ for $a \geq a_{\min} > 0$ and $k > 2$ and $G_\theta(\theta) = 1 - (\theta_{\min} / \theta)^z$ for $\theta \geq \theta_{\min} > 0$ and $z > 2$, $k > 2$, respectively.

This production function depends upon the productivity of the firm (θ), the average of abilities in a firm ($\bar{a}$), and the number of workers hired (h). The average of abilities in the production function makes the firm screen workers with abilities below the cut-off. If the firm fires the workers with abilities below the cut-off, the effect of increased average of abilities in a firm could exceed the effect of the decreased number of workers. With a Pareto distribution of worker abilities, the average of abilities in a firm is $\bar{a} = k a_c / (k-1)$. Since the average of abilities in a firm is dependent on a screening cut-off a_c, the firm will determine this cut-off through paying the screening costs.

[16] In Blanchflower, Oswald, and Sanfey (1996) explains the positive relationship between profit and wage. This rent-sharing model is relevant in U.S. manufacturing because Estevao and Tevlin (2003) find a substantial amount of rent sharing. In particular, Cunat and Guadalupe (2009) show that import penetration affects the compensation structure through changing the sensitivity of pay to performance in the sample on U.S. executives.

This paper also uses screening costs in Helpman, Itskhoki, and Redding (2008). It assumes that if the firm paid a screening cost of ca_c^{δ}/δ, it could screen the workers with abilities below a_c inside and outside of the firm. Since the firm needs costlier tests for higher abilities cutoffs, screening costs are the increasing function of ability cutoff a_c chosen by the firm. Therefore, we can think that setting the cut-off is related with the firm's productivity. Also, the firm confronts other costs. The production is involved with a fixed production cost of f_d. For serving the foreign market, the firm incurs a fixed exporting cost of f_x and variable trade costs. Particularly, this variable trade cost takes the iceberg form, such that $\tau > 1$ units of a variety must be shipped in order for one unit to arrive in the other country.

Now, we can build the profit function, $\pi = (1 - I_x \tau) py - \sum_{i=c}^{h+c} w_i - \frac{c}{\delta} a_c^{\delta} - f_d - I_x f_x$. Also, worker's utility is assumed as the function of individual wage. Therefore, in the bargaining model where the firm and its individual employee choose over wage and employment status, the maximization problem is as follows:

$$Max \sum_{i=c}^{h+c} \phi(a_i) \log(u(w_i) - u(\overline{w})) + (1 - \sum_{i=c}^{h+c} \phi(a_i)) \log \pi \tag{1}$$

where $u(w_i)$ is a worker i's utility from wage w_i and $\overline{w}$ is the wage available from temporary work in the event of a breakdown in bargaining. Then, since temporary work does not reflect the returns to abilities, $\overline{w}$ can be interpreted as general compensation for education and experience in the economy. ϕ is the bargaining power of an employee. Here, the bargaining power is determined by abilities a_i because the firm takes longer to replace the worker with higher abilities and the firm is likely to earn zero in the event of a bargaining delay. Although the above maximization problem has three choice variables such as h, a_c, and w_i, this paper derives the first-order condition with respect to w_i because the introduction of worker heterogeneity makes the maximum problem more complicated with respect to h and a_c. Furthermore, the first-order condition with respect to w_i is enough to understand how the residual wage is determined and so construct the estimation equation.

At an interior optimum, the following first-order condition with respect w_i to hold:

$$w_i : \ \frac{\phi(a_i)u'(w_i)}{[u(w_i) - u(\overline{w})]} - \frac{1 - \sum_{i=c}^{h+c} \phi(a_i)}{\pi} = 0 \tag{2}$$

Rewrite the first of these as

$$\frac{u(w_i) - u(\overline{w})}{u'(w_i)} = \left(\frac{\phi(a_i)}{1 - \sum_{i=c}^{h+c} \phi(a_i)} \right) \pi \tag{3}$$

This can be simplified by using $u(\overline{w}) \cong u(w_i) + (\overline{w} - w_i)u'(w_i)$ to produce the equilibrium residual wage as followings:

$$w_i - \overline{w} \cong \left(\frac{\phi(a_i)}{1 - \sum_{i=c}^{h+c} \phi(a_i)} \right) \pi . \tag{4}$$

The equation (4) is useful for understanding how the residual wage is determined. It shows that, to a first-order approximation, the equilibrium residual wage is determined by the profit and the relative bargaining strength between the firm and its individual employee according to an employee's ability; that is, it reflects the compensation for workers' abilities that are evaluated by a firm. This is similar to Lemieux (2006)'s interpretation that the residual wage is the product of abilities with the return to abilities. Therefore, the residual wage implies that workers with the same education level and experience could be paid differently according to the firm's productivity or profit. Moreover, workers with the same education level and experience in the same firm could be paid differently according to their performance.

From equation (4), we can know that the profit and the bargaining power affect the slope in the relationship between the residual wage and abilities. Therefore, we can set up the schedule of the residual wage to abilities in an exporting firm and a non-exporting firm. <Figure 1> shows these schedules in low degree of openness:

<<Figure 1>>

a_c^n is the cut-off point of a non-exporting firm; if a worker had abilities less than the cut-off, the worker would be unemployable. As workers have higher abilities, their returns to them will be higher in both an exporting and a non-exporting firm. The difference of the two slopes implies that an exporting firm can make more profit and better offers. Due to low degree of openness, the difference of the two slopes is not huge. Therefore, the workers ($a > a_c^n$) in a non-exporting firm have less motivation to move toward an exporting firm.[17]

[17] This is similar to "Cross-Skill Matching" equilibrium. Davidson, Matusz, and Shevchenko (2008) defines it as one in which high-skill workers are willing to accept low-tech jobs. Additionally, they define an "Ex-Post Segmentation" equilibrium as one in which skilled workers are not willing to do so.

Additionally, an exporting firm will invest more a screening mechanism to identify workers with abilities below the cut-off in order to obtain inside and outside workers with high abilities. That is, due to paying the additional cost such as exporting fixed cost and transportation cost, an exporting firm should be more productive and so need workers with high abilities. Therefore, the cut-off point of an exporting firm (a_c^e) is higher than that of a non-exporting firm.

Through <Figure 2>, we can know how the distribution of residual wage is changed as the economy becomes more open to trade. Higher degree of trade openness in the country where intra-industry trade dominates implies higher import penetration and higher export propensity in the same industry. First of all, the impact of increased import penetration on residual wages is shown by arrows (1) and (2) in <Figure 2>. When import penetration increases, the higher competition in the domestic market requires a non-exporting firm to have workers with higher abilities. Thus, the cut-off of a non-exporting firm increases by $\overline{a_c^n}$.[18] Consequently, the workers with abilities below the new cut-off and the workers in marginal firms will be unemployed. This effect of increased imports (arrow (2)) raises the average residual wage as <Figure 2>. However, there is the other effect of increased imports (arrow (1)). The import penetration also makes the curve of non-exporting firms shift downward because the reduced domestic market share causes decreasing profit. Therefore,

[18] In different way, increased import penetration pushes up the cut-off of a non-exporting firm productivity (θ). Therefore, since survived non-exporting firms are likely to have a higher screening cut-off, the new cut-off ($\overline{a_c^n}$) is higher than a_c^n.

the impact of increased imports on the average residual wage depends on the magnitude of the two effects; that is, *when job destruction below the new cut-off (* $\overline{a_c^n}$ *) occurs more, the effect of the shifting downward curve on the average residual wage is decreased.*

<<Figure 2>>

Furthermore, arrows (3) and (4) represent the influence of increased export propensity. Higher degree of trade openness implies that the existing exporters can sell more abroad and some non-exporting firms can start to export, which implies the increases in an exporting firm's profit and labor demand. Therefore, an exporting firm's slope shifts outwardly (arrow (3)) and the cut-off of an exporting firm lowers because the decrease in export costs enables a non-exporting firm with slightly below the cut-off to join the foreign markets (arrow (4)). In particular, the gap between an exporter's slope and a non-exporter's slope is widening. As a result, the workers with ability above $\overline{a_c^e}$ in exporting firms have more motivation to move toward exporting firms because of high compensation for their ability.[19] At this point, the important thing is that the job creation in incumbent and newly exporting firms accelerates this process. This implies that exporting firms are likely to search for workers with abilities above the cut-off in the pool of the employed rather than the pool of the unemployed.[20] *As job creation in exporting firms increases, the impact of exports on the*

[19] This implies that the economy moves from a "Cross-Skill Matching" equilibrium to an "Ex-Post Segmentation" in Davidson, Matusz, and Shevchenko (2008).

[20] Menezes Filho and Muendler (2007) show the interesting evidence that tariff cuts and additional imports trigger worker displacements, but that neither comparative-advantage sectors nor exports absorb trade-displaced worker. This evidence implies that an exporting firm searches its workers in the pool of employed, rather than unemployed.

residual wage also increases.

The implications derived from this conceptual framework shed an important light on constructing the estimation model in Section 3 and interpreting the results of regressions in Section 4.

III. Data and Estimation Strategy

Data Description

The best way to examine the impact of job flow induced by trade on the average residual wage in section II is to use a matched employee-employer dataset. However, generally, the matched employee-employer datasets cannot be available publicly. To answer the main question empirically, I combine several data sets: Merged Outgoing Rotation Groups Current Population Survey (MORG-CPS), U.S. Trade by Feenstra (1998), Job Creation and Destruction by Foster, Haltiwanger, and Kim (2006), and Manufacturing Industry Productivity Database by Bartelsman, Becker, and Gray (2000).

The CPS is a monthly household survey conducted by the Bureau of Labor Statistics to gather information on the labor force characteristics of the U.S. population. According to Cameron and Trivedi (2005), households are interviewed in four consecutive months, ignored for eight months, and then interviewed again for another four months. The CPS-MORG consists of households in their 4th and 8th interview among them. Lemieux (2006) shows that this data is more reliable than alternative sources of wage data such as March CPS because it provides a less noisy measure of the key variable of interest (compensation per hour). In addition, the CPS-MORG has larger observations than PSID or March/May CPS.[21] This is important because I restrict the sample to full-time male workers aged 16 to 64 in the manufacturing sector. This paper also attempts to divide the industry by using narrower classification, and therefore obtains 74 categories of industry.[22]

For information on wage, I use hourly wages in the CPS-MORG because theories of wage determination are closely connected with the hourly wage rate.[23] Real hourly wage is calculated by using Consumer Price Index (CPI). Like Lemieux (2006), I trim extreme values of wages (less than $1 and more than $100 in 1979 dollars) and weigh wage observations using the CPS weights. Top-coded weekly and hourly wages also are multiplied by a factor of 1.4.[24] I draw the distribution of real hourly wage for full-time male workers in the manufacturing sector in both 1983 and 1994 by using the kernel density method. Panel (a) in <Figure 3> shows that the hourly real wage in 1994 is more dispersed than in 1983 as suggested in many studies on inequality of real hourly wage.

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[21] The MORG supplement is roughly three times as large as the May or March supplements of the CPS.

[22] CPS has its own industry classification based on SIC code. There are some sectors which cannot be divided by SIC87 3-digit. So I merge them; that is, primary aluminum industry and other primary metal industry are merged; scientific and controlling instruments industry and medical, dental, and optical instrumental and supplies industry are also merged. And, I exclude leather tanning and finishing industry and watches, clocks and clockwork operated devices industry because the observations is not enough. However, as compared with early literatures, this industry classification is very narrow and heterogeneous in terms of cross-section. For example, Revenga (1992) use 38 three- and four-digit SIC (narrower, wage, employment also negative).

[23] If hourly wage were absent and only weekly wages were recorded, it would be defined as weekly wages divided by usual weekly hours for salaried workers.

[24] There are several ways to control top-coded weekly and hourly wage. DiNardo, Fortin, and Lemieux (1996) use the upper tail of the 1986 distribution of wages to impute a wage distribution to the observations censored at the top-code in other years. Also, according to the CPS questionnaire, it recommends them to be removed.

The observable skills such as education and experience are required to obtain the residual wage. When we use schooling as a regressor in wage equations, the CPS has one well-known problem that schooling is not measured in a consistent questionnaire over time; that is, after 1992, a question about the highest graduate attended switched to the highest grade or diploma completed, instead of asking whether the highest grade was completed. Nonetheless, Lemieux (2006) suggests the possible way to construct a relatively consistent variable for years of schooling completed over the whole sample period. In his manner, this paper classifies years of schooling completed into the nine groups as like 0-4, 5-8, 9, 10, 11, 12, 13-15, 16, and 17+. Also, the experience can be measured by a proxy variable, age.

Additionally, from the CPS-MORG, we can obtain the union density rate across industries in order to reflect the labor market condition. Other indexes are the import penetration and export propensity from Feenstra (1998), the job destruction and job creation index from Foster, Haltiwanger, and Kim (2006), and the real shipment from Bartelsman, Becker, and Gray (2000). They are measured by SIC 4-digit, so I match them into the CPS industry classification based on SIC 3-digit.[25] Since information on union in the MORG-CPS exists after 1983 and Feenstra provides us with trade index until 1994, the sample period in this paper is from 1983 to 1994.

The real hourly wage, education, and experience variables enable us to estimate the

[25] In matching trade index and job flow index, I use output and employment in Bartelsman, Becker, and Gray (2000) dataset as weights.

residual wage. In the sample of full-time male workers in the manufacturing sector, the residuals come from separate regressions of the logarithm of real hourly wages on a set of age, a quadratic in age, and nine schooling dummies for each year.[26] <Table 1> is the estimation result of the Mincerian wage equation. The row of Stdev, the standard deviation of coefficients of eight schooling dummies, shows that the inequality among premiums of schooling year is increasing. Particularly, the last row implies that the college premium is also increasing as shown in early literature.[27] In addition, panel (b) in <Figure 3> shows the distribution of full time male workers' residual wages in both 1983 and 1994. Similar to panel (a) in <Figure 3>, the distribution in 1994 is more dispersed.

Furthermore, I draw the cumulative distribution functions for residual wages in several industries in order to capture the impact of import penetration in industries with different labor market conditions. <Figure 4> and <Figure5> show the cumulative distribution functions of residual wages in the industries with a high change rate of import penetration. However, the industries in <Figure 4> have a high change rate of job destruction, while the industries in <Figure 5> are characterized as a low change rate of job destruction.[28] Compared to <Figure 4>, the 1994 residual wage distributions in <Figure 5> are located

[26] Lemieux (2006) uses the interactions between schooling dummies and a quadratic in age in order to improve R^2. This paper does not use interactions in order to emphasize that residual wages imply differences within a group with the same education and experience.

[27] Here, the college premium is calculated by subtracting the coefficient of ed6 from that of ed8. Since ed7 is 13-15 years of schooling completed, it is not relevant for college premium. Therefore, the paper assumes that 16 years of schooling is the bachelor degree. The college premium is the difference of wage between graduates from high school and ones from college.

[28] The logging industry and the office and accounting machines industry in <Figure 4> are amongst the top five industries for change rate of job turnover. Although the job turnover reflects the labor market rigidity well, however, I use the job destruction index in order to connect them with <Figure 2>.

wholly in the left of 1983 residual wage distributions. Additionally, the 1994 cumulative distribution functions in <Figure 5> have a longer left-tail than the 1983 ones. These provide suggestive support for the role of arrow (1) and arrow (2) in <Figure 2>. As a result, we can know that a high change rate of job destruction enables an industry exposed to highly increased imports to have fewer workers with low residual wage. Additionally, <Table 2> reports the minimum, average, and maximum values of variables in order to calculate the marginal effects.

Estimation Strategy

This paper introduces the dependent variables such as average and 10th percentile of estimated residual wages at the industry level.[29] These dependent variables also enable us to capture the response of residual wage distribution characteristics to trade. The equation (5) is the starting point in order to capture the impact of imports and exports on the residual wage.

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 uni_{s,t} + \beta_3 \ln imp_{s,t} + \beta_4 \ln \exp_{s,t} + \beta_5 \ln rship_{s,t} + \varepsilon_{s,t} \qquad (5)$$

where $Rw_{s,t}$ is the average, or 10th of the residual wage in the industry s at time t; $uni_{s,t}$ is the union density of industry s at time; $\ln imp_{s,t}$ is the logarithm of import penetration ratio of industry s at time t; $\ln \exp_{s,t}$ is the logarithm of export propensity ratio of

[29] This strategy has an advantage to avoid the Moulton problem. If we construct the estimation equation with individual-level dependent variable and industry-level independent variables, the Moulton problem would make the standard errors underestimated. According to Angrist and Pischke (2009), using group averages instead of microdata is a good way to avoid the Moulton problem.

industry s at time t; $\ln rship_{s,t}$ is the logarithm of real shipment of industry s at time t; $\varepsilon_{s,t}$ is consisted of the s industry-specific effect (ν_s), the time-specific effect (δ_t), and the error-term ($\eta_{s,t}$). In particular, the logarithm of real shipment controls for third factors such as changes in consumer's taste and technology. Therefore, the addition of real industrial shipment enables trade openness in empirical model to be more closely connected with trade liberalization in Melitz (2003).

To answer the main question in this paper, however, we need to modify the equation (5). In the comparison of <Figure 4> with <Figure 5>, we can know the distributional consequence of import penetration on individual residual wages is dependent on the level of job destruction. It gives us the intuition about how to make the empirical equations in order to identify the role of each arrow in <Figure 2>. To reflect this intuition, I modify the equation (5) into (6)-(8) by adding interaction terms with the union density, job destruction and job creation, respectively. However, while running the regression of the 10th percentile of residual wage, I use the equation (5)-(7) to identify the arrow (2) in <Figure 2>.

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 uni_{s,t} + \beta_3 \ln imp_{s,t} + \beta_4 \ln imp_{s,t} * uni_{s,t} + \beta_5 \ln \exp_{s,t} + \beta_6 \ln \exp_{s,t} * uni_{s,t} + \beta_7 \ln rship_{s,t} + \varepsilon_{s,t} \quad (6)$$

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 neg_{s,t} + \beta_3 \ln imp_{s,t} + \beta_4 \ln imp_{s,t} * neg_{s,t} + \beta_5 \ln \exp_{s,t} + \beta_6 \ln rship_{s,t} + \varepsilon_{s,t} \quad (7)$$

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 pos_{s,t} + \beta_3 \ln imp_{s,t} + \beta_4 \ln \exp_{s,t} + \beta_5 \ln \exp_{s,t} * pos_{s,t} + \beta_6 \ln rship_{s,t} + \varepsilon_{s,t}$$

(8)

where $neg_{s,t}$ is the job destruction of industry s at time t; $pos_{s,t}$ is the job creation of industry s at time t.

Although the CPS is the repeated cross-section, I can construct industry-level panel data in order to estimate the equation (5)-(8). Then, the MORG-CPS consists of households in their 4th and 8th interview. So some interviewers are likely to be observed between two years. Since this makes the sample persistent, I use the dynamic panel analysis. The dynamic model permits regressors to include lagged dependent variables, which causes the endogeneity problem.[30] Moreover, the reverse causality between the residual wage and job flow in the equation may occur; that is, the increase of residual wage in exporting firms causes high-ability workers in non-exporting firms to move toward exporting firms voluntarily, which affects job destruction positively. This also engenders the endogeneity problem. Additionally, according to Cameron and Triviedi (2005), the measurement error induces the endogeneity problem in building the industry-level panel data with individual-level data set.

The endogeneity problems presented above suggest the system GMM estimator. The main strength of this estimator is to provide more consistent and efficient estimates in the presence of endogeneity problems.[31] The system GMM estimator is proposed by Blundell

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[30] The fixed effects estimates of the lagged dependent variable can be severely biased downwards for small T as Nickell (1981) shows.
[31] Collado (1997) suggests the GMM estimator in order to remove the endogeneity problem induced by the

and Bond (1998) in order to overcome a significant shortcoming of the first-difference GMM estimator by Arellano and Bond (1991). According to Blundell and Bond, the instruments used with the first-difference GMM estimator become less informative in models where the variance of the fixed effects is high relative to the variance of the transitory shocks. This engenders biased coefficients, and furthermore this problem becomes worse in a small sample. However, the system GMM estimator is expected to have much smaller finite sample bias because of combining in a system the first-differenced with the same equation expressed in levels.[32] Especially, this paper uses the standard error adjusted by the Windmeijer (2005) finite sample correction in order to reduce finite sample bias additionally.

Since the system GMM estimator is not a panacea, two criteria and one possible problem should be noted. First of all, the system GMM estimator needs to satisfy two criteria: the test for serial correlation in the first-differenced errors and the Sargan test for overidentifying restrictions. Since a system has first-differences, the first test is to check whether serial correlation exists among the error terms, as proposed by Arellano and Bond (1991). The other, Sargan test, evaluates whether instruments in this paper are valid. This could suffer from the problem that should be noted.

One possible problem stems from using all the available moment conditions, which

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measurement error in Pseudo-panel. The sample in this paper has the characteristics of pseudo-panel because of aggregating the individual observations by year and industry.

[32] According to Hayakawa (2007), the system GMM is less biased than the first difference and the level GMM estimator. Since the level GMM estimator has an upward bias and the difference GMM estimator has a downward bias, both biases cancel each other out in the system GMM.

is called as overfitting biases. Bowsher (2002) shows that the use of too many instruments in GMM estimation causes the p-value of the Sargan test to be close to 1. This implies that the power of the Sargan test can be lost. To correct this problem, this paper restricts instrument sets by not using lags further back than $t-4$. This could improve the power of the test for overidentifying restrictions in spite of losing the efficiency of the estimates due to fewer instrument variables.

Therefore, I regard the system GMM as the preferred estimator. Since this data set aggregates the individual observation by year and industry, all reported standard errors and test statistics are heteroskedasticity-robust. In the case of the within estimator, I correct the standard errors by using a bootstrapping procedure.

IV. Empirical Results

The empirical results are presented in <Table 3-4>. Each table presents the estimation results based on OLS (column 1), within (column 2), and system GMM (column 3-5) estimator. Also the first three columns in each table estimate equation (5) without the interaction term, while the next three columns estimate equations (6)-(8) with the interaction. As mentioned above, I will interpret the estimation results based on the preferred estimator, the system GMM.

Before interpreting the results, this paper has to evaluate the system GMM estimator in terms of the validity of instruments and the model specification. All three diagnostic statistics in <Table 3-6> are satisfactory; that is, the Sargan test does not reject the over-identification restrictions; the absence of first order serial correlation is rejected while the absence of second order serial correlation is not rejected. Then, I am also concerned with overfitting biases and finite sample bias for the system GMM estimator. To avoid overfitting biases, I do not use any lags dated further back than $t-4$, and so all tables in this paper obtain the Sargan test P-value much smaller than 1. In the case of finite sample bias, Bond (2002) suggests a useful fact: since the OLS and within estimator are biased in opposite directions, the coefficients on the lagged dependent variable estimated by a consistent estimator should lie between the OLS and within estimates. All coefficients on the lagged dependent variable in <Table 3-4> using system GMM are in this interval. This implies that finite sample bias associated with weak instruments is not present. In particular, Windmeijer's (2005) corrected standard error reduces finite sample bias. Therefore, all coefficients estimated by system GMM are consistent without problems.

Looking at column 3 in <Table 3>, the first point to note is that increases in import penetration are associated with decreases in average residual wage, while increases in export propensity are associated with increases in average residual wage. Specifically, an import penetration elasticity of -0.011 in column 3 is significantly different from zero at the 10% level. Also the export propensity elasticity in column 3 is 0.016 and significantly different from zero at the 5% level. And the long-run effect of import penetration and export propensity are -0.044 (SE=0.024) and 0.064 (SE=0.027), respectively.[33] [34] That is, the export propensity elasticity is larger than the import penetration elasticity. If the volume of export is similar to that of imports, it implies that trade could raise the average residual wage.

However, the above implication depends on the labor market conditions as suggested in section II. Let's focus attention on column 4-6 in <Table 3a>. In column 4, I attempt to capture the role of the labor market by interacting the union density with import penetration and export propensity, respectively. The column 4 in <Table 3a> shows that the interaction term between union density and import penetration is negative and statistically significant at the 10% level. This implies that the union density could be the crucial channel through which increased imports affect the average residual wage. In order to shed additional light on the quantitative importance of union density, I calculate the partial derivates of import penetration, i.e. the marginal effect. The marginal effect of import penetration varies depending on the level of the union density. To gauge the range of variation, I calculate the derivatives of import penetration at the minimum, median and maximum values of union density. These are presented respectively in <Table 3b>. According to first column in <Table 3b>, the marginal effects of import penetration decrease, and even change from negative to

[33] The long-run effect is calculate as follow; the long-run effect of an import penetration elasticity is $\beta_3/(1-\beta_1)$ =-0.011/(1-0.755)=-0.044 in column 3; the long-run effect of an export propensity is 0.016/(1-0.755)=0.064. The standard errors in the long-run effect are computed by the Delta-method.

[34] Despite of significance of those coefficients, the size of coefficient is somewhat small relatively to Revenga (1992) with the import price elasticity of 0.06. The possible explanation is different data set. Contrary to this paper, Revenga (1992) uses the quarterly import price for the index of import competition.

positive as the union density declines. Interestingly, with high union density, the effect of trade on average residual wage is likely to be negative because the impact of imports exceeds that of exports.[35]

<Figure 2> dealt with in section II makes us understand this evidence more clearly. This evidence implies that if the union negatively affects the firm's decision to fire workers below the cut-off, the denser the union would be in increased imports, the more the average residual wage would be affected by the arrow (1) than by the arrow (2) in <Figure 2>. The union tends to preserve jobs through wage concessions. Furthermore, when the union bargains with the firm instead of individual workers, the union is likely to prevent the firm from sorting the workers according to abilities; that is, the firm with a denser union cannot fire the workers with abilities below the cut-off through sorting. Therefore, it dampens the effect of arrow (2) in <Figure 2>. As a result, higher union density in the industry with increased imports is likely to decrease the average residual wage.

Column 5 in <Table 3a> suggests more interesting evidence. Here, I use the index of job destruction in order to capture the impact of arrow (2) in <Figure 2> directly. The interaction term is positive and statistically significant at the 5% level, while import penetration is negative and statistically significant at the 1% level. This result can correspond to <Figure 2> well. Similar to the case of union density, I calculate the marginal effect of

[35] When the union density has the maximum value, the import penetration elasticity is -0.024 and the export propensity elasticity is 0.011. Therefore, -0.024 + 0.011 = -0.013.

import penetration at the minimum, median and maximum values of job destruction. The first column in <Table 3c> shows them. The marginal effects of import penetration increase and change from negative to positive as job destruction happens more. That is, when increased imports take the marginal firms and marginal workers out of the market through increasing the cut-off of productivity and abilities respectively, the effect of job destruction can offset the decrease in average residual wage induced by decreasing profits. It is especially similar to the cleansing effect because the workers with abilities below the cut-off become unemployed. In comparing with the coefficient of export propensity, we can know that the less job destruction happens, the more likely the effect of trade on average residual wage is to be negative because the impact of imports exceeds that of exports.[36]

Additionally, column 6 in <Table 3a> shows that the impact of exports on the average residual wage also depends on the labor market conditions. Increased exports raise the residual wages in exporting firms because of increased profit as suggested in the equation (4). Also, exporting firms attempt to hire more workers with abilities above the cut-off. The job creation in the industry with increased exports is likely to raise the average residual wage because exporting firms can make better offers than non-exporting firms. According to column 6 in <Table 3a>, the interaction term between exports and job creation is positive and statistically significant at the 10% level. This implies the increase of average residual wage

[36] When the job destruction has the minimum value, the import penetration elasticity is -0.036. The export propensity elasticity in column 5 is 0.021. Therefore, -0.036 + 0.021 = -0.015.

explained by the arrow (4) in <Figure 2>. Particularly, the second column in <Table 3c> implies that as job creation occurs more, the magnitude of the marginal effect of export propensity is increasing. Particularly, the more job creation happens, the more likely the effect of trade on average residual wage is to be positive because the impact of exports dominates that of imports.[37]

This evidence can be supported by analyzing the workers located in the lowest percentile of residual wage distribution. Thus this paper pays more attention to 10th percentile of residual wage distribution. <Table 4a> shows the results from regression of the 10th percentile of residual wages. Interestingly, the evidence in <Table 4a> shows a similar pattern as <Table 3a>. Specifically, the interaction term between import and job destruction in column 5 is positive and statistically significant at the 1% level, while $\ln import_{s,t}$ is negative and statistically significant at the same level. According to the marginal effect of import penetration in <Table 4b>, the job destruction causes the sizable variation of this marginal effect. That is, the job destruction plays a critical role in raising the 10th percentile of residual wage. If there were the selection effect of import penetration on the workers with ability below the cut-off, the 10th percentile of residual wage would be raised by import penetration. Therefore, as more job destruction occurs, the left-tail of residual wage distribution will be cut. This will push up the average residual wage.

[37] When the job creation has the maximum value, the export propensity is 0.043. The import penetration elasticity in column 6 is -0.015. Therefore, 0.043 - 0.015 = 0.028.

In order to connect those evidences to Melitz (2003) argument, this paper has to examine the impact of trade on the average industrial wage including the average predicted wage and residual wage. Therefore, I turn attention to the impact of trade on the average predicted wage. <Table 5> reports the results from regressions of the average predicted wage on trade. According to column 3 in <Table 5>, import penetration and export propensity are statistically insignificant in the 10% level. We can expect this from the fact that the Mincerian wage equation does not reflect industrial characteristics. In sum, the impact of trade on the average industrial wage is determined only by the residual wage; that is, with high union density, low job destruction, and low job creation, the effect of trade on the average wage is likely to be negative. Therefore, trade liberalization in the more rigid labor market is unlikely to induce the selection effect and so worker's welfare would not be raised in the long-run.

V. Robustness Check

To check the robustness of above results, this section employs the size of tariff as another way to measure trade liberalization. Therefore, this paper examines the impact of U.S. import weighted average tariffs on the average and 10th percentile of residual wages by using the following equations.

$$Rw_{s,t} = \alpha + \beta_1 Rw_{s,t-1} + \beta_2 \ln rship_{s,t} + \beta_3 uni_{s,t} + \beta_4 \ln tariff_{s,t} + \varepsilon_{s,t} \tag{9}$$

$$\begin{aligned} Rw_{s,t} &= \alpha + \beta_1 Rw_{s,t-1} + \beta_2 \ln rship_{s,t} + \beta_3 pos_{s,t} + \beta_4 neg_{s,t} + \beta_5 \ln tariff_{s,t} \\ &+ \beta_6 \ln tariff_{s,t} * pos_{s,t} + \beta_6 \ln tariff_{s,t} * neg_{s,t} + \varepsilon_{s,t} \end{aligned} \tag{10}$$

where $\ln tariff_{s,t}$ is the logarithm of tariff of industry s at time t.[38] However, in the 10^{th} percentile regression, the job creation variables ($pos_{s,t}$ and $\ln tariff_{s,t} * pos_{s,t}$) are excluded because the 10^{th} percentile regression is designed to identify the arrow (2) in <Figure 2>.

According to results, the logarithm of tariffs is negatively but insignificantly associated with the average residual wage. This insignificance could be explained by the fact that since the decreased tariffs are likely to imply the increased imports and increased exports, the impacts of imports on the residual average wage could be offset by that of exports, and vice versa. However, the column 2 in <Table 6a> and the column 1 in <Table 6b> show that as job creation and job destruction are higher, the impact of tariffs on the residual wage is more sizable and significant.

The regression of 10^{th} percentile of residual wages can support these results. The column 3 in <Table 6a> shows that the logarithm of tariff negatively and significantly affects the 10^{th} percentile of residual wages; that is, the lower the tariff is, the higher the 10^{th} percentile of residual wage is. Furthermore, the column 4 in <Table 6a> reports that the interaction term between tariff and job destruction is negative and statistically significant at the 5% level. This interaction term can capture the arrow (2) in <Figure 2>, which implies that the active job destruction is the crucial channel through which the trade liberalization measured by tariffs affects the 10^{th} percentile of residual wage. Specifically, the marginal

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[38] The variable of tariff means U.S. import weighted tariffs (duties/custom value). Schott provides this dataset on his website (http://www.som.yale.edu/faculty/pks4/sub_international.htm).

effect of tariffs shows that the magnitude of this marginal effect is increasing as job destruction is high. These results are consistent with the impact of trade openness on the average and 10^{th} percentile of residual wages.

VI. Conclusion

Under which labor market conditions does trade raise the average real industrial wage? This paper shows that with low union density, high job destruction, and high job creation, trade would raise the average real industrial wage. In fact, job creation is closely related with job destruction. According to Scarpetta et al (2002), the employment protection legislation (EPL) prevents new firms from entering the market because of higher firing costs. It is two sides of the same coin. That is, more job destruction can induce more job creation. Therefore, as trade is liberalized more, job turnover is more important in order to work the selection effect of trade in Melitz (2003).

This implication sheds a crucial light on the study about trade and aggregate productivity. Melitz and Ottaviano (2008) and Archaya and Keller (2008) suggest that trade can lower the aggregate productivity under unilateral trade and high entry barriers, respectively. In particular, the high entry barrier in Archaya and Keller (2008) can be connected to the demand of labor, the job creation. Therefore, as suggested in this paper, the labor market condition can be the important link; that is, if the rigidity in the labor market incurs high firing costs, trade would lower the average real industrial wage and the selection effect of trade in Melitz (2003) would never happen. As a result, the more trade increases, the more the labor market conditions matter for aggregate industry productivity dynamics and the worker's long-run welfare.

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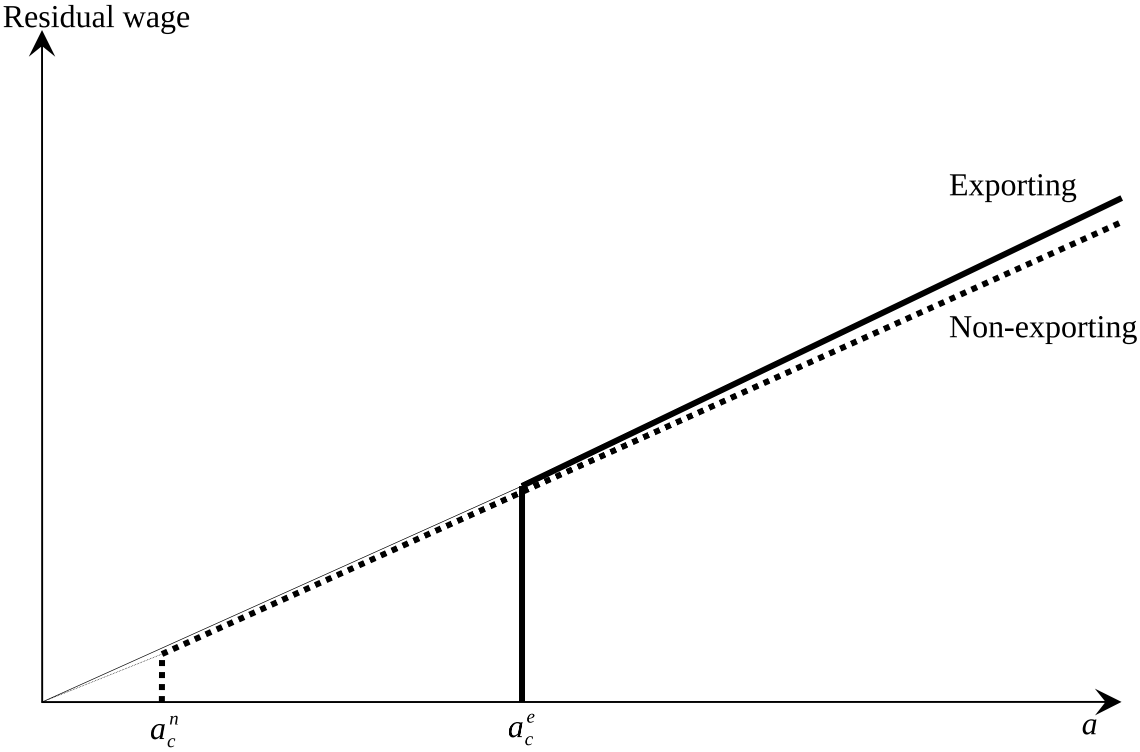
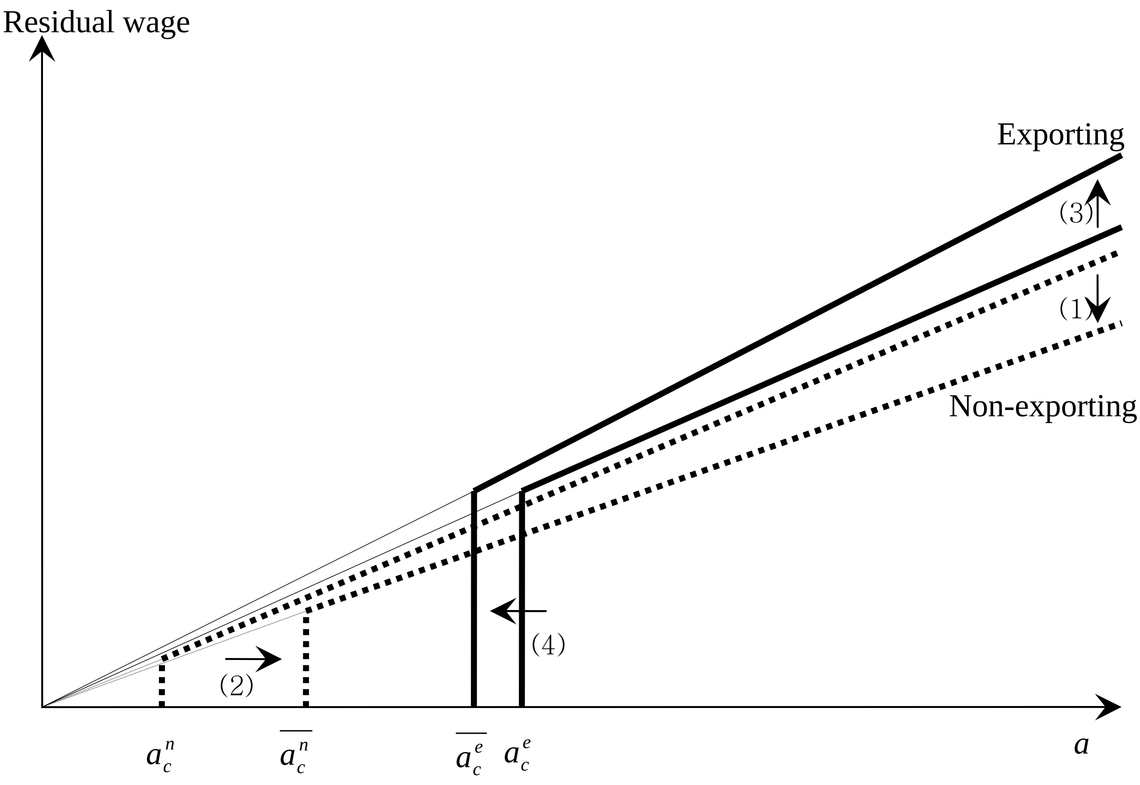
<Figure 1> The schedule of the residual wage to abilities in low degree of trade openness



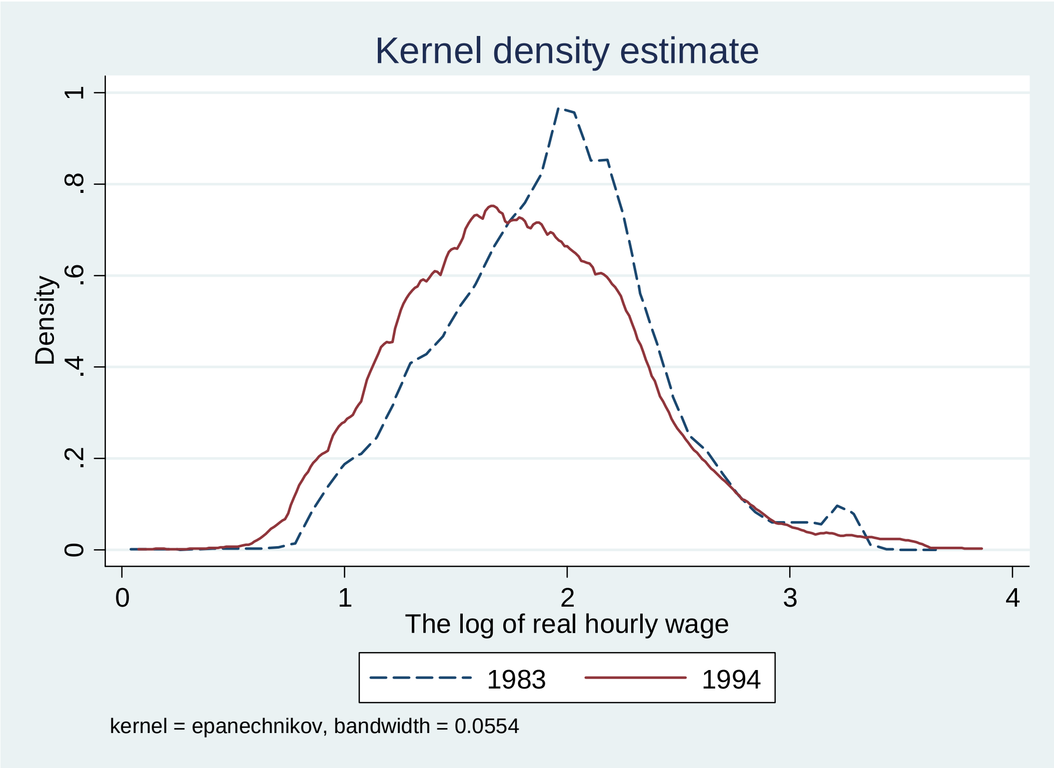
<Figure 2> The schedule of the residual wage to abilities in higher degree of trade openness



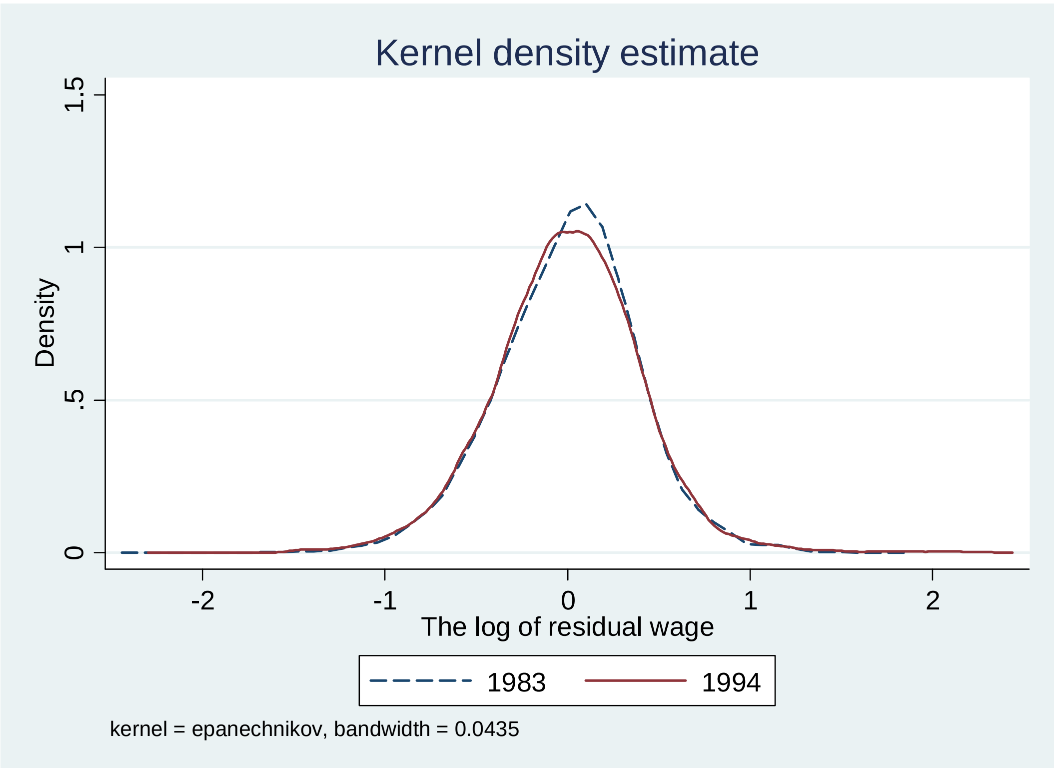
Notes: a_c^n is the cut-off of non-exporting firm. a_c^e is the cut-off of exporting firm.

<Figure 3> The distribution between 1983 and 1994 in the manufacturing sector

Panel (a): real hourly wage

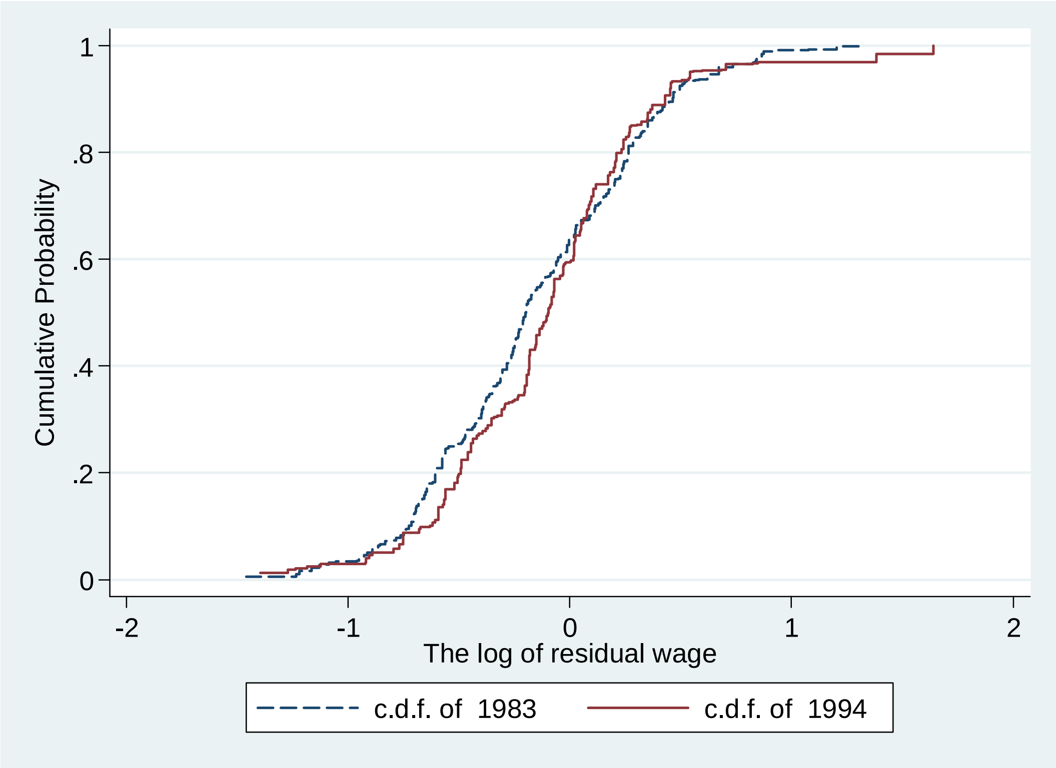


Panel (b): residual real hourly wage

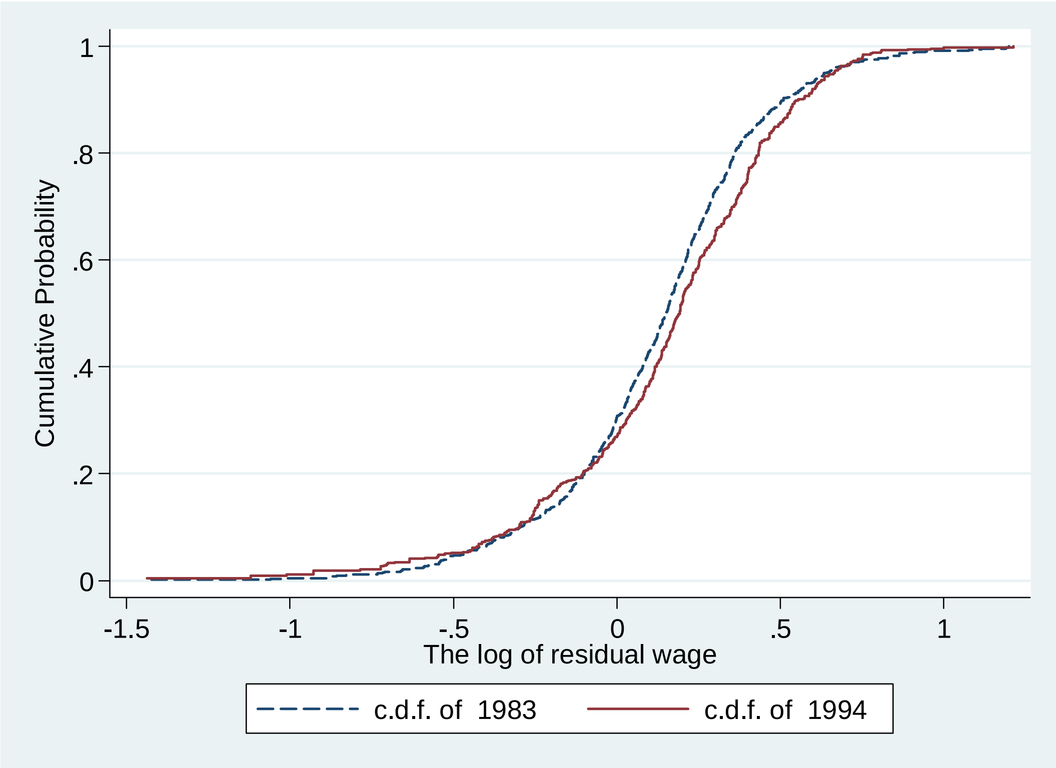


<Figure 4> Cumulative distribution functions of residual wages between 1983 and 1994 in the industries with a high change rate of import penetration and job destruction

Panel (a): Logging industry

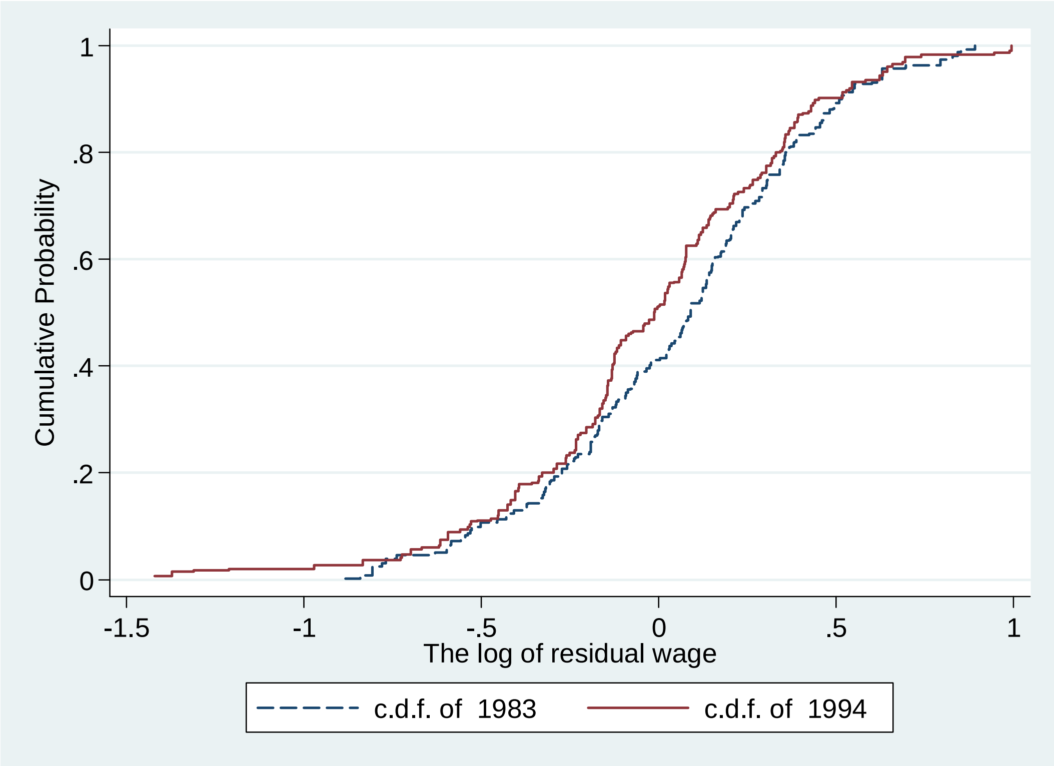


Panel (b): Office and Accounting machines industry

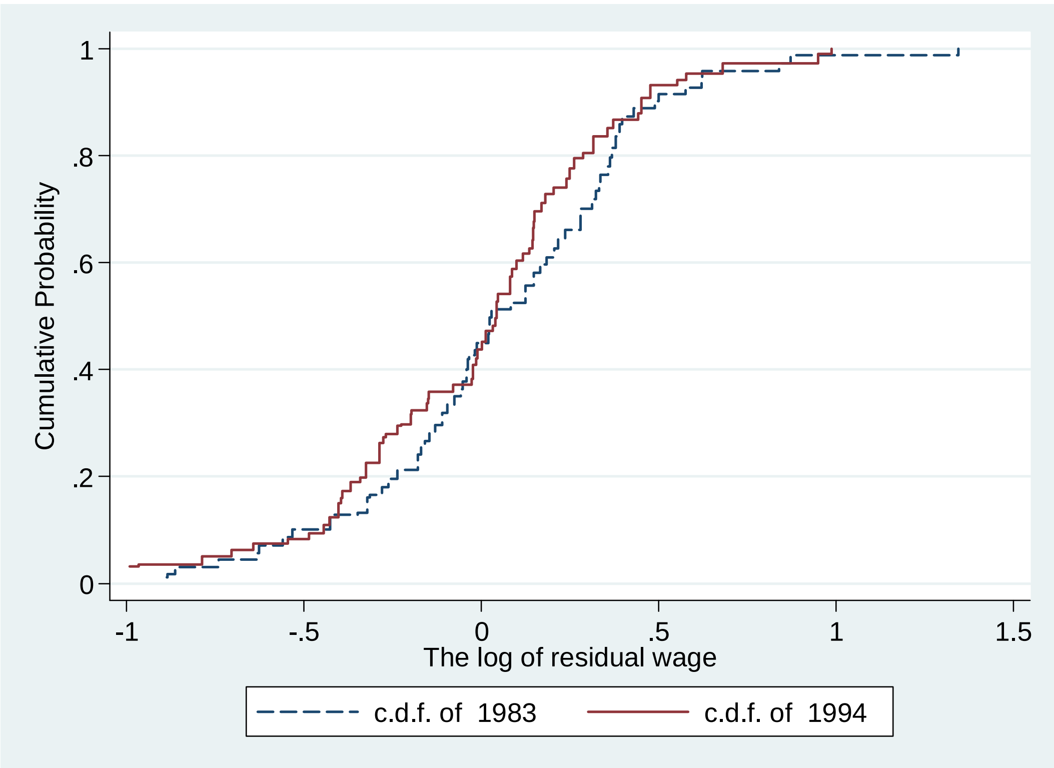


<Figure 5> Cumulative distribution functions of residual wages between 1983 and 1994 in the industries with a high change rate of import penetration but a low change rate of job destruction

Panel (a): Plastics, Synthetics and Resins industry



Panel (b): Paints, Varnishes and related industry



<Table 1> Regression results of a Mincerian equation.

	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994
Exp	0.065	0.065	0.066	0.067	0.064	0.064	0.063	0.061	0.06	0.06	0.061	0.063
Exp2	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006	-0.0006
ed2	0.157	0.172	0.173	0.228	0.194	0.143	0.076	0.093	0.087	0.131	0.104	0.114
ed3	0.269	0.252	0.253	0.294	0.268	0.237	0.208	0.214	0.167	0.201	0.219	0.178
ed4	0.313	0.324	0.333	0.344	0.313	0.326	0.25	0.248	0.236	0.277	0.277	0.23
ed5	0.361	0.355	0.396	0.418	0.385	0.345	0.271	0.274	0.298	0.300	0.307	0.288
ed6	0.482	0.489	0.497	0.531	0.515	0.467	0.394	0.399	0.422	0.448	0.422	0.433
ed7	0.617	0.613	0.638	0.688	0.676	0.614	0.552	0.574	0.585	0.595	0.582	0.577
ed8	0.846	0.853	0.897	0.958	0.946	0.91	0.819	0.847	0.861	0.939	0.912	0.897
ed9	0.992	1.041	1.066	1.124	1.126	1.058	1.009	1.038	1.062	1.125	1.118	1.151
cons	-0.10	-0.13	-0.17	-0.25	-0.19	-0.15	-0.08	-0.08	-0.12	-0.16	-0.18	-0.23
R2	0.357	0.372	0.381	0.396	0.399	0.388	0.384	0.401	0.397	0.396	0.399	0.388
n	22528	23483	23600	23127	22518	21517	21855	22364	20966	20109	19438	18575
Stdev[b]	0.293	0.305	0.315	0.325	0.337	0.326	0.324	0.333	0.347	0.361	0.356	0.370
(ed8-ed6)[c]	0.364	0.364	0.400	0.427	0.431	0.443	0.425	0.448	0.439	0.491	0.490	0.464

Notes: [a]:Exp is the experience measured by a proxy variable, age. And the nine schooling dummies are for 0-4, 5-8, 10, 11, 12, 13-15, 16, and 17+. In order to avoid multicollinearity, the dummy for 0-4 is excluded. [b]:Stdev is the standard deviation of coefficients of ed2-ed9. [c]:(ed8-e6) represents the college premium.

<Table 2> Summary Statistics

	Obs.	Average	St.Dev.	Min	Max.
Average of log(residual wage)	888	-0.028	0.107	-0.347	0.273
10^{th} percentile of log(residual wage)	888	-0.500	0.132	-1.119	-0.042
Log(real shipment)	888	23.76	1.068	20.403	26.311
Union density	888	0.256	0.140	0	0.684
Import penetration	888	0.131	0.134	0.000032	0.800
Export propensity	888	0.084	0.086	0.000001	0.575
Tariff	876	0.047	0.036	0	0.228
Job creation	888	8.083	3.270	1.303	26.119
Job destruction	888	10.527	4.875	1.738	47.841

<Table 3a> Regression results: Dependent variable = Average residual wage

	OLS	Within	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
$Rwage_{s,t-1}$	0.846***	0.231***	0.755***	0.737***	0.785***	0.772***
	(0.019)	(0.071)	(0.079)	(0.086)	(0.084)	(0.087)
$\ln ship_{s,t}$	0.0024	0.0069	0.0031	0.0048	0.00021	-0.0038
	(0.0021)	(0.025)	(0.0036)	(0.0079)	(0.0075)	(0.0068)
$uni_{s,t}$	0.023*	0.091**	0.125	0.00034		
	(0.013)	(0.044)	(0.088)	(0.108)		
$neg_{s,t}$					0.0020	
					(0.0021)	
$pos_{s,t}$						0.0052
						(0.0039)
$\ln import_{s,t}$	-0.0035*	-0.0051	-0.011*	0.0091	-0.039***	-0.015*
	(0.0018)	(0.0078)	(0.0062)	(0.0099)	(0.014)	(0.0078)
$\times uni_{s,t}$				-0.053*		
				(0.028)		
$\times neg_{s,t}$					0.0019**	
					(0.00089)	
$\ln export_{s,t}$	0.0043**	0.0101*	0.016**	0.0034	0.021**	0.0027
	(0.0019)	(0.0053)	(0.0060)	(0.015)	(0.0083)	(0.0065)
$\times uni_{s,t}$				0.012		
				(0.040)		
$\times pos_{s,t}$						0.0015*
						(0.00086)
R2 / Time	0.811/O	0.693/ O	./ O	./O	./O	./O
Obs.	814	814	814	814	814	814
AR(1)/AR(2)	/	/	0.00/0.599	0.00/0.569	0.00/0.466	0.00/0.471
Sargan			0.712	0.850	0.786	0.691

Notes: [a]: Robust standard errors are reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively. [b]: The standard errors in Within are corrected using a bootstrapping procedure. [c]: This system-GMM uses lags up to *t*-4 as instruments to avoid overfitting biases.

<Table 3b> Marginal effects of import penetration and export propensity in column 4

	Import	Export
Min	0.0078(0.0093)	0.0037(0.014)
Median	-0.0032(0.0068)	0.0063(0.0074)
Max	-0.024(0.013)*	0.011(0.012)

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 3c> Marginal effects of import penetration in column 5 and export propensity in column 6

	Import	Export
Min	-0.036(0.013)***	0.0047 (0.0060)
Median	-0.022(0.0079)***	0.015 (0.0065)**
Max	0.030(0.022)	0.043 (0.020)**

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 4a> Regression results: Dependent variable = 10th-percentile residual wage

	OLS	Within	SYS-GMM	SYS-GMM	SYS-GMM
$Rw_{s,t-1}$	0.644***	0.017	0.300**	0.317**	0.511***
	(0.041)	(0.054)	(0.147)	(0.153)	(0.168)
$\ln rship_{s,t}$	0.0077*	-0.0078	0.012	0.020	0.0069
	(0.0045)	(0.076)	(0.015)	(0.022)	(0.019)
$uni_{s,t}$	0.124***	0.201***	0.368*	-0.055	
	(0.030)	(0.059)	(0.214)	(0.285)	
$neg_{s,t}$					0.00003
					(0.0037)
$\ln import_{s,t}$	-0.0056	0.00020	-0.0047	0.0091	-0.059***
	(0.0040)	(0.0095)	(0.013)	(0.021)	(0.015)
$\times uni_{s,t}$				-0.092*	
				(0.055)	
$\times neg_{s,t}$					0.0033***
					(0.0013)
$\ln export_{s,t}$	0.0098**	0.011	0.029**	0.030*	0.057***
	(0.0040)	(0.0071)	(0.015)	(0.017)	(0.016)
R2 / TimeDummy	0.564/O	0.140/O	./ O	./O	./O
Obs.	814	814	814	814	814
AR(1)/AR(2)	/	/	0.01/0.209	0.005/0.219	0.00/0.132
Sargan			0.384	0.398	0.762

Notes: [a]: Robust standard errors are reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively. [b]: The standard errors in Within are corrected using a bootstrapping procedure. [c]: This system-GMM uses lags up to *t*-4 as instruments to avoid overfitting biases.

<Table 4b> Marginal effects of import penetration in column 4 and 5

	Column 4 (union)	Column 5 (job destruction)
Min	0.0067 (0.020)	-0.053 (0.014)***
Median	-0.012 (0.018)	-0.028 (0.012)**
Max	-0.051 (0.030)*	0.065 (0.039)*

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.

<Table 5> Regression results: Dependent variable = Average predicted wage

	OLS	Within	SYS-GMM
$Rw_{s,t-1}$	0.945(0.017) ***	0.292(0.051)***	0.893(0.050)***
$\ln rship_{s,t}$	0.0031(0.002)	0.024(0.038)	0.0041(0.0024)*
$uni_{s,t}$	-0.0017(0.0090)	-0.0047(0.027)	0.052(0.087)
$\ln imp_{s,t}$	-0.00094(0.0014)	-0.0064(0.0062)	-0.004(0.007)
$\ln \exp_{s,t}$	0.0013(0.0014)	0.00087(0.0049)	0.0090(0.0061)
R2 / TimeDummy	0.894 / Yes	0.622 / Yes	. / Yes
Obs.	814	814	814
AR(1) / AR(2)			0.00 / 0.516
Sargan			0.399

Notes: [a]: Robust standard errors are reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively. [b]: The standard errors in Within are corrected using a bootstrapping procedure. [c]: This system-GMM uses lags up to *t*-4 as instruments to avoid overfitting biases.

<Table 6a> Regression results of Tariff: Dependent variable = Average residual wage and 10^{th}-percentile residual wage

Dependent variable	Average	Average	10^{th}	10^{th}
	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
$Rwage_{s,t-1}$	0.829***	0.858***	0.463***	0.473***
	(0.060)	(0.074)	(0.132)	(0.106)
$\ln rship_{s,t}$	0.0043**	0.0041	0.0024	0.013*
	(0.0021)	(0.0026)	(0.020)	(0.0071)
$uni_{s,t}$	0.057		0.169	
	(0.056)		(0.167)	
$neg_{s,t}$		0.000023		0.0080*
		(0.0016)		(0.0045)
$pos_{s,t}$		0.0068*		
		(0.0040)		
$\ln tariff_{s,t}$	-0.018	0.424	-0.689**	0.917
	(0.199)	(0.527)	(0.315)	(0.849)
$\times neg_{s,t}$		-0.012		-0.142**
		(0.021)		(0.068)
$\times pos_{s,t}$		-0.060		
		(0.047)		
R2 / Time	./ O	./O	./ O	./O
Obs.	803	803	803	803
AR(1)/AR(2)	0.00/0.778	0.00/0.498	0.00/0.160	0.00/0.217
Sargan	0.790	0.838	0.500	0.504

Notes: [a]: Robust standard errors are reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively. [b]: The standard errors in Within are corrected using a bootstrapping procedure. [c]: This system-GMM uses lags up to *t*-7 as instruments to avoid overfitting biases.

<Table 6b> Marginal effects of tariff in column 3 and 4

	Column 2 (job turnover)	Column 4 (job turnover)
Min	0.268(0.416)	0.549(0.689)
Median	-0.154(0.178)	-0.414(0.354)
75^{th}	-0.317(0.178)*	-0.806(0.322)**
Max or 99^{th}	-0.9302(0.558)*	-2.476(0.889)***

Notes: Standard errors are calculated by delta method and reported in brackets. Significant variables at 10%, 5%, and 1% significance level are marked with *, **, and ***, respectively.